

Degree-distribution stability of scale-free networks

Zhenting Hou^{1*}, Xiangxing Kong^{1*}, Dinghua Shi^{1,2†}, and Guanrong Chen^{3‡}

¹*School of Mathematics, Central South University, Changsha 410083, China*

²*Department of Mathematics, Shanghai University, Shanghai 200444, China*

³*Department of Electronic Engineering, City University of Hong Kong, Hong Kong, China*

(Dated: May 10, 2008)

Based on the concept and techniques of first-passage probability in Markov chain theory, this letter provides a rigorous proof for the existence of the steady-state degree distribution of the scale-free network generated by the Barabási-Albert (BA) model, and mathematically re-derives the exact analytic formulas of the distribution. The approach developed here is quite general, applicable to many other scale-free types of complex networks.

PACS numbers: 89.75.Hc, 05.70.Ln, 87.23.Ge, 89.75.Da

Introduction. The intensive study of complex networks is pervading all kinds of sciences today, ranging from physical to biological, even to social sciences. Its impact on modern engineering and technology is prominent and will be far-reaching. Typical complex networks include the Internet, the World Wide Web, wired and wireless communication networks, power grids, biological neural networks, social relationship networks, scientific cooperation and citation networks, and so on. Research on fundamental properties and dynamical features of such complex networks has become overwhelming.

In the investigation of various complex networks, the degree distributions are always the main concerns because they characterize the fundamental topological properties of the underlying networks.

Noticeably, for a ring-shape regular graph^[1] of whatever size, where every vertex is connected to its K nearest-neighboring vertices, all vertices have the same degree K . For the well-known Erdős-Rényi random graph model^[2] with n vertices and m edges, the degree distribution of vertices is approximately Poisson with mean value $2m/n$. For the small-world network proposed by Watts and Strogatz^[1], the degree distribution of vertices also follows Poisson distribution approximately.

A common feature of the above models is that the degree distribution of vertices has a characteristic size $\langle k \rangle$. In contrast, Barabási and Albert^[3] found that for many real-world complex networks, e.g., the WWW, the fraction $P(k)$ of vertices with degree k is proportional over a large range to a “scale-free” power-law tail: $k^{-\gamma}$, where γ is a constant independent of the size of the network. Thus, the fraction $P(k)$ of vertices with degree k is referred to as the degree distribution of a scale-free network. To explain this phenomenon, they proposed the following network-generating mechanism^[3], known as the BA model:

“... starting with a small number (m_0) of vertices, at every time step we add a new vertex with m ($\leq m_0$) edges that link the new vertex to m different vertices already present in the system. To incorporate preferential attachment, we assume that the probability Π that a new vertex will be connected to a vertex depends on the connectivity k_i of that vertex, so that $\Pi(k_i) = k_i / \sum_j k_j$. After t steps the model leads to a random network with $t + m_0$ vertices and mt edges.”

In [3], computer simulation showed that for the BA model the degree distribution of the network has a power

law form with the exponent $\gamma = 2.9 \pm 0.1$. In [4], a heuristic argument based on the mean-field theory led to an analytic solution $P(k) \sim 2m^2k^{-3}$, namely $\gamma = 3$. To derive the following dynamic equation:

$$\frac{\partial k_i}{\partial t} = m\Pi(k_i) = \frac{k_i}{2t}, \quad k_i(i) = m,$$

it was assumed^[4] that the probability (can be interpreted as a continuous rate of change of k_i) for an existing vertex with degree k_i to receive a new connection from the new vertex is exactly equal to $m\Pi(k_i)$, which is simultaneously proportional to both the degree $k_i(t)$ of the existing vertex i and the number m of the new edges that the new vertex brings in, at time t . For notational convenience, this assumption will be simply referred to as the “ $m\Pi$ -hypothesis” in this paper.

In all the consequent works related to the BA model, this $m\Pi$ -hypothesis plays a fundamental role. For example, Krapivsky et al.^[5] replaced the degree $k_i(t)$ of vertex i at time t by the total number $N_k(t)$ of degree- k vertices over the whole network at time t , thereby obtaining its rate equation

$$\frac{dN_k(t)}{dt} = m \frac{(k-1)N_{k-1}(t) - kN_k(t)}{\sum_k kN_k(t)} + \delta_{km},$$

where δ_{km} accounts for new vertices bringing in new edges. In this study, the $m\Pi$ -hypothesis was adopted in the derivations. Assuming that the steady-state degree distribution exists, using the law of large numbers ($\frac{N_k(t)}{t} \rightarrow P(k)$ as $t \rightarrow \infty$), they showed that the difference equation of $P(k)$ has an analytic solution

$$P(k) = \frac{4}{k(k+1)(k+2)}$$

for the BA model with $m = 1$. They also pointed out that only the linear preferential attachment scheme can lead to the scale-free structure but any nonlinear one will not.

Dorogovtsev et al.^[6] considered $k_i(t)$ as a random variable and defined $P(k, i, t)$ to be the probability that vertex i has exactly k edges at time t , where vertex i is the vertex that was being added to the network at time $t = i$, $i = 1, 2, \dots$. Moreover, they used the average of all vertex degrees as the network degree: $P(k, t) \triangleq \frac{1}{t} \sum_{i=1}^t P(k, i, t)$. They introduced a more general attraction model and allowed multiple edges between vertices,

where each new vertex has an initial attraction degree A . Simultaneously, m new directed edges coming out from non-specified vertices are introduced with the probability Π , therefore $k = A + q$ with q being the in-degree of vertices. Consequently, when every new vertex is the source of the m new edges like in the BA model, the attraction model makes more sense than the BA model. They first arrived at the master equation of $P(k, i, t)$ and then by summing all i 's together they were able to derive the following equation:

$$P(k, t+1) = \frac{k-1}{2t} P(k-1, t) + \left(1 - \frac{k}{2t}\right) P(k, t) + \delta_{mk} + O\left(\frac{P(k, t)}{t}\right).$$

To that end, by assuming the existence of $P(k)$ [note that actually an additional assumption of $\lim_{t \rightarrow \infty} t[P(k, t+1) - P(k, t)] = 0$ is also needed], they obtained a difference equation for $P(k)$. Finally, solving the equation gave an analytic solution

$$P(k) = \frac{2m(m+1)}{k(k+1)(k+2)}.$$

Here, it should be pointed out that if multiple edges are not allowed, then the $m\Pi$ -hypothesis is still needed.

As a side note, Dorogovtsev et al.^[7] also considered the effect of accelerating growth, which is proportional to the power of the time variable t at each time step. However, this destroys the scale-free feature and degree-distribution stability of the network.

Afterwards, Bollobás^[8] made a general comment on the BA model:

“From a mathematical point of view, however, the description above, repeated in many papers, does not make sense. The first problem is getting started. The second problem is with the preferential attachment rule itself, and arises only for $m \geq 2$. In order to prove results about the BA model, one must first decide on the details of the model itself. It turns out to be convenient to allow multiple edges and loops.”

Consequently, he and his coauthors recommended a so-called LCD model, as follows:

“We start with the case $m = 1$. Consider a fixed sequence of vertices v_1, v_2, \dots . We shall inductively define a random graph process $\{G_1^t\}_{t \geq 0}$ so that G_1^t is a directed graph on $\{v_i : 1 \leq i \leq t\}$, as follows. Start with G_1^0 the “graph” with no vertices, or with G_1^1 the graph with one vertex and one loop. Given G_1^{t-1} , form G_1^t by adding the vertex v_t together with a single edge directed from v_t to v_i , where i is chosen randomly with

$$\Pi(i = s) = \begin{cases} \frac{d_{G_1^{t-1}}(v_s)}{2t-1}, & 1 \leq s \leq t-1 \\ \frac{1}{2t-1}, & s = t. \end{cases}$$

For $m > 1$ we define the process $\{G_m^t\}_{t \geq 0}$ by running the process $\{G_1^t\}$ on a sequence v'_1, v'_2, \dots ; the graph G_m^t is formed from G_1^{mt} by identifying the vertices v'_1, v'_2, \dots, v'_m to form v_1 , identifying $v'_{m+1}, v'_{m+2}, \dots, v'_{2m}$ to form v_2 , and so on.”

For graph G_m^n , let $\#_m^n(d)$ be the number of vertices of G_m^n with in-degree equal to d , i.e., with (total) degree $m + d$, and set

$$a_{m,d} = \frac{2m(m+1)}{(d+m)(d+m+1)(d+m+2)}.$$

Bollobás et al.^[9] rigorously proved the following result:

$$\lim_{n \rightarrow \infty} E[\#_m^n(d)]/n = a_{m,d}.$$

Then, based on the martingale theory, they proved that $\#_m^n(d)/n$ converges to $a_{m,d}$ in probability.

It has been observed that most real-world and simulated networks follow certain rules to add or remove their vertices and edges, which are not entirely random. More importantly, at each time step, these rules are applied only to the previously formed network, therefore the process has prominent Markovian properties. Shi et al.^[10] established a close relationship between the BA model and Markov chains. According to the evolution of the BA model, the degree $k_i(t)$ of vertex i at time t constitutes a nonhomogeneous Markov chain as time evolves. Thus, all vertices together form a family of Markov chains. Consequently, based on the Markov chain theory, starting from an initial distribution and iteratively multiplying the state-transition probability matrices, the final network degree distribution can be easily obtained. Lately, Shi et al.^[11] developed an evolving network model by using an anti-preferential attachment mechanism, which can generate scale-free networks with power-law exponents varying between $1 \sim 4$. There are several modified and generalized BA models in the literature, including such as the local-world BA model^[12], which will not be listed and reviewed here.

All in all, the BA model indeed is a breakthrough discovery with significant impact on network science today. Therefore, it is quite important to support the model with a rigorous mathematical foundation.

It is clear from the above discussions that two key questions need to be carefully answered for the BA model: 1) For the case of $m \geq 2$, can one find a scheme of adding new edges from the new vertex to the existing ones that has a probability precisely equal to $m\Pi$? This is the key of the BA modeling. 2) Does the steady-state degree distribution of the network exist and, if so, what is it? This is the key to the validity of the mean-field, rate-equation, master-equation, and Markov-chain approaches. The present paper will give complete answers to these two questions.

Degree-distribution stability. To start, consider the first question. Recall that Holme and Kim^[13] proposed a scheme for new edge connection: When a new vertex comes into the network, the first edge connects to an existing vertex with the preferential attachment probability Π . After that, the rest $m-1$ edges randomly connect with probability p to the vertices in the neighborhood of the vertex that the first edge was connected to, or connect with probability $1-p$ to those vertices that the first edge did not connect to. Here, consider this approach with $p = 1$ in the following scenario: When a new vertex

comes into the network, the first edge connects to an existing vertex with the specified preferential attachment probability Π , same as above. Yet, the rest $m - 1$ edges simultaneously connect to $m - 1$ vertices randomly chosen from inside the neighborhood of the vertex that the first edge was connected to. By random sampling theory this is equivalent to the above Holme-Kim scheme which continually connects the edges to $m - 1$ vertices randomly chosen from inside the neighborhood without allowing multiple edges. For this special scheme, the following result can be rigorously proved.

Proposition. For the BA model with the above special attachment scheme, if vertex i has degree $k_i(t)$ at time t , then the probability that vertex i receives a new edge from the new vertex at time $t + 1$ is exactly equal to $m\Pi(k_i)$.

Proof. Let $P_i(t+1)$ be the probability of vertex i receiving a new edge from vertex $t + 1$ at time $t + 1$. Then,

$$\begin{aligned} P_i(t+1) &= \frac{k_i(t)}{\sum_j k_j(t)} + \sum_{l \in O_i(t)} \frac{k_l(t)}{\sum_j k_j(t)} \frac{C_{k_i(t)-1}^{m-2}}{C_{k_l(t)}^{m-1}} \\ &= \frac{k_i(t)}{\sum_j k_j(t)} + \sum_{l \in O_i(t)} \frac{m-1}{\sum_j k_j(t)} = m \frac{k_i(t)}{\sum_j k_j(t)}, \end{aligned}$$

where

$$\frac{C_{k_i(t)-1}^{m-2}}{C_{k_l(t)}^{m-1}} = \frac{(k_i(t)-1)!/[(m-2)!(k_i(t)-m+1)!]}{k_l(t)!/[(m-1)!(k_l(t)-m+1)!]} = \frac{m-1}{k_l(t)},$$

which is the probability of choosing vertex i , among the $m - 1$ vertices that were randomly chosen from inside the neighborhood $O_l(t)$ of vertex l , to perform simultaneous connections.

The Proposition answers the first question posted above and shows that the special Holme-Kim preferential attachment scheme is one way to implement the $m\Pi$ -hypothesis.

In order to prove the degree-distribution stability of the general BA network, the BA model is specified first. Start with a complete graph with m_0 vertices, which has a total degree $N_0 = m_0(m_0 - 1)$, and denote these vertices by $-m_0, \dots, -1$, respectively. In all the following derivations, the $m\Pi$ -hypothesis will be assumed. The general BA networks will be further discussed in the last section below.

Following Dorogovtsev et al.^[6], consider the degree $k_i(t)$ as a random variable, and let $P(k, i, t) = P\{k_i(t) = k\}$ be the probability of vertex i having degree k at time t , and moreover let the network degree distribution be the average over all its vertices at time t , namely,

$$P(k, t) \triangleq \frac{1}{t + m_0} \sum_{i=-m_0, i \neq 0}^t P(k, i, t).$$

Recall that $k_i(t)$ is a random variable for any fixed t and it is a nonhomogeneous Markov chain for variable t ^[10]. Under the $m\Pi$ -hypothesis, the state-transition probability of this Markov chain is given by

$$P\{k_i(t+1) = l \mid k_i(t) = k\} = \begin{cases} 1 - \frac{k}{2t + \frac{N_0}{m}}, & l = k \\ \frac{k}{2t + \frac{N_0}{m}}, & l = k + 1 \\ 0, & \text{otherwise,} \end{cases} \quad (1)$$

where $k = 1, 2, \dots, m + t - i$, and $i = 1, 2, \dots$.

The existence of the steady-state degree distribution for this specified BA network can be proved in three steps as follows. Detailed derivations are supplied in the Appendix of the paper.

1. Consider the first-passage probability of the Markov chain:

$$f(k, i, t) = P\{k_i(t) = k, k_i(l) \neq k, l = 1, 2, \dots, t - 1\}.$$

Then, the relationship between the first-passage probability and the vertex degrees is established.

Lemma 1. Under the $m\Pi$ -hypothesis, for the BA model with $k > m$,

$$f(k, i, s) = P(k - 1, i, s - 1) \frac{k - 1}{2(s - 1) + \frac{N_0}{m}}, \quad (2)$$

$$P(k, i, t) = \sum_{s=i+k-m}^t f(k, i, s) \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right). \quad (3)$$

2. Under the $m\Pi$ -hypothesis, using the state-transition probability of the Markov chain, one first finds the expression of $P(m, t)$, as follows:

$$\begin{aligned} P(m, t) &= \prod_{i=1}^{t-1} \left(1 - \frac{m}{2i + \frac{N_0}{m}}\right) \frac{i + m_0}{i + 1 + m_0} \\ &\quad \times \left[P(m, 1) + \sum_{l=1}^{t-1} \frac{\frac{1}{l+1+m_0}}{\prod_{j=1}^l \left(1 - \frac{m}{2j + \frac{N_0}{m}}\right) \frac{j+m_0}{j+1+m_0}} \right] \\ &= \frac{1}{t + m_0} \prod_{i=1}^{t-1} \left(1 - \frac{m}{2i + \frac{N_0}{m}}\right) \\ &\quad \times \left[(1 + m_0)P(m, 1) + \sum_{l=1}^{t-1} \prod_{j=1}^l \left(1 - \frac{m}{2j + \frac{N_0}{m}}\right)^{-1} \right]. \end{aligned}$$

Then, one can show the existence of the limit $\lim_{t \rightarrow \infty} P(m, t)$ by using the following classical Stolz-Cesàro Theorem in Calculus.

Stolz-Cesàro Theorem^[14]. In sequence $\{\frac{x_n}{y_n}\}$, assume that $\{y_n\}$ is a monotone increasing sequence with $y_n \rightarrow \infty$. If the limit $\lim_{n \rightarrow \infty} \frac{x_{n+1} - x_n}{y_{n+1} - y_n} = l$ exists, where $-\infty \leq l \leq +\infty$, then $\lim_{n \rightarrow \infty} \frac{x_n}{y_n} = l$.

Lemma 2. Under the $m\Pi$ -hypothesis, for the BA model, the limit $\lim_{t \rightarrow \infty} P(m, t)$ exists and is independent of the initial network:

$$P(m) \triangleq \lim_{t \rightarrow \infty} P(m, t) = \frac{2}{m + 2} > 0. \quad (4)$$

3. Under the $m\Pi$ -hypothesis, similarly, one finds the expression of $P(k, t)$ using the first-passage probability of the Markov chain, and then shows the existence of the limit $\lim_{t \rightarrow \infty} P(k, t)$ by using the Stolz-Cesàro Theorem, if the limit $\lim_{t \rightarrow \infty} P(k - 1, t)$ exists.

Lemma 3. Under the $m\Pi$ -hypothesis, for the BA model with $k > m$, if the limit $\lim_{t \rightarrow \infty} P(k - 1, t)$ exists then the limit $\lim_{t \rightarrow \infty} P(k, t)$ also exists:

$$P(k) \triangleq \lim_{t \rightarrow \infty} P(k, t) = \frac{k - 1}{k + 2} P(k - 1) > 0. \quad (5)$$

Finally, by mathematical induction, it follows from Lemmas 2 and 3 that the steady-state degree distribution of the specified BA network exists. To this end, by solving the difference equation (5) iteratively, one arrives at the following conclusion.

Theorem 1. Under the $m\Pi$ -hypothesis, for the BA model with $k \geq m$, the steady-state degree distribution exists, independent of the initial network, and is given by

$$P(k) = \frac{2m(m+1)}{k(k+1)(k+2)} \sim 2m^2 k^{-3} > 0. \quad (6)$$

Clearly, this degree distribution formula is consistent with the formula obtained by Dorogovtsev et al.^[6] and Bollobás et al.^[9], which allow multiple edges and loops.

Discussion. Bollobás^[8] once discussed the BA description (the $m\Pi$ -hypothesis) of preferential attachment in detail. His result gives a range of models fitting the BA description with very different properties. When $m \geq 2$, as a new vertex comes in, it is no problem for its first edge to preferentially connect to an existing vertex. But what about the other $m - 1$ new edges? This question was not carefully addressed before. Clearly, after the first edge has been connected from the new vertex to an existing vertex, the preferential attachment probability Π is no longer the same if later operations do not allow multiple edges and loops. It is also clear that when $m \geq 2$, the probability of vertex i receiving a new edge is always greater than Π . But what is it? On the other hand, it is also possible that the probability of vertex i receiving a new edge depends on other vertex degrees. Barabási always emphasizes the $m\Pi$ -hypothesis but did not discuss this “how” question either. Thus, two questions arise: 1) For the BA model, or for any other BA-like model, how to prove the degree-distribution stability if the $m\Pi$ -hypothesis holds only approximately? 2) Is there a preferential attachment scheme for $m \geq 2$ such that the probability of vertex i receiving a new edge is independent of other vertex degrees?

To answer these two questions, a new preferential attachment scheme is proposed and discussed in [15], where

a new vertex will be simultaneously connected to m different vertices and it is assumed that the preferential attachment probability Π is proportional to the sum of the degrees k_{i_1}, \dots, k_{i_m} of those vertices. They showed that the probability that the existing vertex i received an edge from the new vertex is independent of other vertex degrees, namely,

$$\Pi_m^{t+1}(k_i(t)) = \frac{m_0 + t - m}{m_0 + t - 1} \frac{k_i(t)}{2mt + N_0} + \frac{m - 1}{m_0 + t - 1},$$

where m_0 is the number of vertices and N_0 is the total degree in the initial network. Consequently, under the $(a_t k_i(t) + b_t)(1 + o(1))_{k_i(t), t}$ -hypothesis and some mild conditions, they proved the degree-distribution stability of Barabási-Albert type networks. Especially, the power-law exponent of the network degree distribution in this new preferential attachment scheme is $\gamma = 2m + 1$.

Finally, it should be emphasized that the theory and scheme developed in this paper has great generality^[16], in the sense that it can be applied to many BA-like modified and generalized models, such as the LCD model of Bollobás et al.^[9], the attraction model of Dorogovtsev et al.^[6], the local-world BA-like model of Li and Chen^[12], and the evolving network model of Shi et al.^[11], etc.

We summarize the results and findings in this paper as follows: (1) Our proving method differs from the one based on martingale theory, and can be applied to many other scale-free types of complex networks; (2) We do not need to change the BA model, e.g., to allow multiple edges and loops; (3) We provide a special Holme-Kim preferential attachment scheme such that the “ $m\Pi$ -hypothesis” holds.

This research was supported by the National Natural Science Foundation under Grant No. 10671212, and by the NSFC-HKRGJ Joint Research Projects under Grant N-CityU107/07.

* Email address: zthou@csu.edu.cn

★ Email address: kongxiangxing2008@163.com

† Email address: shidh2001@263.net

‡ Email address: gchen@ee.cityu.edu.hk

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Appendix to “Degree-distribution stability of scale-free networks”

Zhenting Hou¹ Xiangxing Kong¹ Dinghua Shi^{1,2} Guanrong Chen³

¹School of Mathematics, Central South University, Changsha 410083, China

²Department of Mathematics, Shanghai University, Shanghai 200444, China

³Department of Electronic Engineering, City University of Hong Kong, Hong Kong, China

May 10, 2008

To provide a rigorous proof of the degree-distribution stability of the scale-free network generated by the BA model, some parameters are specified as follows: (i) start with a complete graph with m_0 vertices, which has the total degree $N_0 = m_0(m_0 - 1)$, and denote these vertexes by $-m_0, \dots, -1$, respectively; (ii) assume that at each time step t , the probability of the new vertex connecting to an existing vertex i is exactly equal to $m\Pi(k_i(t))$.

Here, in (ii), the preferential attachment probability is simultaneously proportional to both the degree $k_i(t)$ of the existing vertex i and the number m of new edges that the new vertex brings in, at time t . For notational convenience, this assumption will be referred to as the “ $m\Pi$ -hypothesis” below.

Observe that the degree $k_i(t)$ of vertex i at time t is a random variable^[6]. Let $P(k, i, t) = P\{k_i(t) = k\}$ denote the probability of vertex i having degree k at time t , and define the degree distribution of the whole network by the average value of probabilities of vertex degrees

$$P(k, t) \triangleq \frac{1}{t + m_0} \sum_{i=-m_0, i \neq 0}^t P(k, i, t). \quad (1)$$

Observe also that the degree $k_i(t)$ as a process in time t is an nonhomogeneous Markov chain^[10]. Thus, for $k = 1, 2, \dots, t + i - m$, the state transition probabilities of the Markov chain, under the $m\Pi$ -hypothesis, are given by

$$P\{k_i(t+1) = l | k_i(t) = k\} = \begin{cases} 1 - \frac{k}{2t + \frac{N_0}{m}}, & l = k \\ \frac{k}{2t + \frac{N_0}{m}}, & l = k + 1 \\ 0, & \text{otherwise.} \end{cases} \quad (2)$$

1 The BA model with $m = 1$

Denote the first-passage probability of the Markov chain by $f(k, i, t) = P\{k_i(t) = k, k_i(l) \neq k, l = 1, 2, \dots, t-1\}$. First, the relationship between the first-passage probability and the vertex degrees is established.

Lemma 1 For $k > 1$,

$$f(k, i, s) = P(k-1, i, s-1) \frac{k-1}{2(s-1) + N_0}, \quad (3)$$

$$P(k, i, t) = \sum_{s=i+k-1}^t f(k, i, s) \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + N_0}\right). \quad (4)$$

Proof First, consider Eq. (3). The degree of a vertex is always nondecreasing, and increasing at most by 1 each time, according to the construction rule of the BA model. Thus, it follows from the Markovian properties that

$$\begin{aligned} f(k, i, s) &= P\{k_i(s) = k, k_i(l) \neq k, l = 1, 2, \dots, s-1\} \\ &= P\{k_i(s) = k, k_i(s-1) = k-1, k_i(l) \neq k, l = 1, 2, \dots, s-2\} \\ &= P\{k_i(s) = k, k_i(s-1) = k-1\} \\ &= P\{k_i(s-1) = k-1\} P\{k_i(s) = k | k_i(s-1) = k-1\} \\ &= P(k-1, i, s-1) \frac{k-1}{2(s-1) + N_0}. \end{aligned}$$

Second, observe that the earliest time for the degree of vertex i to reach k is at step $k+i-1$, and the latest time to do so is at step t . After this vertex degree becomes k , it will not increase any more. Thus, Eq. (4) is proved.

Lemma 2 (Stolz-Cesàro Theorem) In sequence $\{\frac{x_n}{y_n}\}$, assume that $\{y_n\}$ is a monotone increasing sequence with $y_n \rightarrow \infty$. If the limit $\lim_{n \rightarrow \infty} \frac{x_{n+1} - x_n}{y_{n+1} - y_n} = l$ exists, where $-\infty \leq l \leq +\infty$, then $\lim_{n \rightarrow \infty} \frac{x_n}{y_n} = l$.

Proof This is a classical result, see [14].

Lemma 3 For the probability $P(k, t)$ defined in Eq. (1), the limit $\lim_{t \rightarrow \infty} P(1, t)$ exists and is independent of the initial network; moreover,

$$P(1) \triangleq \lim_{t \rightarrow \infty} P(1, t) = \frac{2}{3} > 0. \quad (5)$$

Proof From the construction of the BA model or Eq. (2), it follows that

$$P(1, i, t+1) = \left(1 - \frac{1}{2t + N_0}\right) P(1, i, t).$$

Since $P(1, t+1, t+1) = 1$, one has

$$\begin{aligned} P(1, t+1) &= \frac{1}{t+1+m_0} \sum_{i=-m_0, i \neq 0}^{t+1} P(1, i, t+1) \\ &= \frac{t+m_0}{t+1+m_0} \left(1 - \frac{1}{2t + N_0}\right) P(1, t) + \frac{1}{t+1+m_0}. \end{aligned}$$

Then, by iteration,

$$\begin{aligned}
P(1, t) &= \prod_{i=1}^{t-1} \left(1 - \frac{1}{2i + N_0}\right) \frac{i + m_0}{i + 1 + m_0} \left[P(1, 1) + \sum_{l=1}^{t-1} \frac{\frac{1}{l+1+m_0}}{\prod_{j=1}^l \left(1 - \frac{1}{2j+N_0}\right) \frac{j+m_0}{j+1+m_0}} \right] \\
&= \frac{1}{t + m_0} \prod_{i=1}^{t-1} \left(1 - \frac{1}{2i + N_0}\right) \left[(1 + m_0)P(1, 1) + \sum_{l=1}^{t-1} \prod_{j=1}^l \left(1 - \frac{1}{2j + N_0}\right)^{-1} \right].
\end{aligned}$$

Next, let

$$x_n \triangleq (1 + m_0)P(1, 1) + \sum_{l=1}^{n-1} \prod_{j=1}^l \left(1 - \frac{1}{2j+N_0}\right)^{-1}$$

and

$$y_n \triangleq (n + m_0) \prod_{i=1}^{n-1} \left(1 - \frac{1}{2i + N_0}\right)^{-1} > 0.$$

Thus, it follows that

$$x_{n+1} - x_n = \prod_{j=1}^n \left(1 - \frac{1}{2j + N_0}\right)^{-1}$$

and

$$y_{n+1} - y_n = \frac{3n + N_0 + m_0}{2n + N_0} \prod_{i=1}^n \left(1 - \frac{1}{2i + N_0}\right)^{-1} > 0.$$

Since $y_n > 0$ and $y_{n+1} - y_n > 0$, $\{y_n\}$ is a strictly monotone increasing nonnegative sequence, hence $y_n \rightarrow \infty$. Moreover,

$$\frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{2n + N_0}{3n + N_0 + m_0} \rightarrow \frac{2}{3} \quad (n \rightarrow \infty).$$

From Lemma 2, one has

$$P(1) \triangleq \lim_{t \rightarrow \infty} P(1, t) = \lim_{n \rightarrow \infty} \frac{x_n}{y_n} = \lim_{n \rightarrow \infty} \frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{2}{3} > 0.$$

This completes the proof.

Lemma 4 For $k > 1$, if the limit $\lim_{t \rightarrow \infty} P(k-1, t)$ exists, then the limit $\lim_{t \rightarrow \infty} P(k, t)$ also exists and, moreover,

$$P(k) \triangleq \lim_{t \rightarrow \infty} P(k, t) = \frac{k-1}{k+2} P(k-1) > 0. \quad (6)$$

Proof First, observe that

$$\begin{aligned} P(k, t) &= \frac{1}{t + m_0} \sum_{i=-m_0, i \neq 0}^t P(k, i, t) \\ &= \frac{1}{t + m_0} \sum_{i=-m_0}^{-1} P(k, i, t) + \frac{t}{t + m_0} \frac{1}{t} \sum_{i=1}^t P(k, i, t). \end{aligned}$$

Next, denote $\bar{P}(k, t) \triangleq \frac{1}{t} \sum_{i=1}^t P(k, i, t)$. One only needs to prove that the limit $\lim_{t \rightarrow \infty} \bar{P}(k, t)$ exists, which will imply that the limit $\lim_{t \rightarrow \infty} P(k, t) = \lim_{t \rightarrow \infty} \bar{P}(k, t)$ exists.

To show that the limit of $\bar{P}(k, t)$ exists as $t \rightarrow \infty$, observe that $P(k, i, t) = 0$ when $i > t + 1 - k$, since in this case even if this vertex i increases its degree by 1 each time, it cannot reach degree k . Then, it follows from Lemma 1 that

$$\begin{aligned} \bar{P}(k, t) &= \frac{1}{t} \sum_{i=1}^{t+1-k} P(k, i, t) \\ &= \frac{1}{t} \sum_{i=1}^{t+1-k} \sum_{s=i+k-1}^t f(k, i, s) \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + N_0}\right) \\ &= \frac{1}{t} \sum_{i=1}^{t+1-k} \sum_{s=i+k-1}^t P(k-1, i, s-1) \frac{k-1}{2(s-1) + N_0} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + N_0}\right) \\ &= \frac{1}{t} \sum_{s=k}^t \sum_{i=1}^{s+1-k} P(k-1, i, s-1) \frac{k-1}{2(s-1) + N_0} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + N_0}\right) \\ &= \frac{1}{t} \sum_{s=k}^t \sum_{i=1}^{s-1} P(k-1, i, s-1) \frac{k-1}{2(s-1) + N_0} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + N_0}\right) \\ &= \frac{1}{t} \sum_{s=k}^t \bar{P}(k-1, s-1) \frac{(s-1)(k-1)}{2(s-1) + N_0} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + N_0}\right) \\ &= \frac{1}{t} \prod_{i=k}^{t-1} \left(1 - \frac{k}{2i + N_0}\right) \left[\bar{P}(k-1, k-1) \frac{(k-1)^2}{2(k-1) + N_0} \right. \\ &\quad \left. + \sum_{l=k}^{t-1} \bar{P}(k-1, l) \frac{l(k-1)}{2l + N_0} \prod_{j=k}^l \left(1 - \frac{k}{2j + N_0}\right)^{-1} \right]. \end{aligned}$$

Next, let

$$\begin{aligned} x_n &\triangleq \bar{P}(k-1, k-1) \frac{(k-1)^2}{2(k-1) + N_0} \\ &\quad + \sum_{l=k}^{n-1} \bar{P}(k-1, l) \frac{l(k-1)}{2l + N_0} \prod_{j=k}^l \left(1 - \frac{k}{2j + N_0}\right)^{-1} \end{aligned}$$

and

$$y_n \triangleq n \prod_{i=k}^{n-1} \left(1 - \frac{k}{2i + N_0}\right)^{-1} > 0 \rightarrow \infty.$$

Obviously,

$$x_{n+1} - x_n = \bar{P}(k-1, n) \frac{n(k-1)}{2n + N_0} \prod_{j=k}^n \left(1 - \frac{k}{2j + N_0}\right)^{-1},$$

and since

$$\begin{aligned} y_{n+1} - y_n &= \left[(n+1) - n \left(1 - \frac{k}{2n + N_0}\right) \right] \prod_{i=k}^n \left(1 - \frac{k}{N_0 + 2i}\right)^{-1} \\ &= \frac{(k+2)n + N_0}{2n + N_0} \prod_{i=k}^n \left(1 - \frac{k}{2i + N_0}\right)^{-1} > 0, \end{aligned}$$

one has that $\{y_n\}$ is a strictly monotone increasing nonnegative sequence, hence $y_n \rightarrow \infty$. Also, by assumption,

$$\frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{(k-1)n}{(k+2)n + N_0} \bar{P}(k-1, n) \rightarrow \frac{k-1}{k+2} P(k-1) \quad (n \rightarrow \infty).$$

Thus, it follows from Lemma 2 that

$$\lim_{t \rightarrow \infty} \bar{P}(k, t) = \lim_{n \rightarrow \infty} \frac{x_n}{y_n} = \lim_{n \rightarrow \infty} \frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{k-1}{k+2} P(k-1) > 0,$$

therefore, $\lim_{t \rightarrow \infty} P(k, t)$ exists, and Eq. (6) is thus proved.

Theorem 1 The steady-state degree distribution of the BA model with $m = 1$ exists, and is given by

$$P(k) = \frac{4}{k(k+1)(k+2)} \sim 4k^{-3} > 0. \quad (7)$$

Proof By mathematical induction, it follows from Lemmas 3 and 4 that the steady-state degree distribution of the BA model with $m = 1$ exists. Then, solving Eq. (6) iteratively, one obtains

$$P(k) = \frac{k-1}{k+2} P(k-1) = \frac{k-1}{k+2} \frac{k-2}{k+1} \frac{k-3}{k} P(k-3).$$

By continuing the process till $k = 3 + 1$, one finally obtains

$$P(k) = \frac{4}{k(k+1)(k+2)} \sim 4k^{-3} > 0.$$

From Theorem 1, one can see that the degree distribution formula of Krapivsky et al.^[5] is exact, although the mathematical proof there was not as rigorous as that given above.

2 The BA model with $m \geq 2$

Lemma 5 Under the $m\Pi$ -hypothesis, the BA model when $k > m$ satisfies

$$f(k, i, s) = P(k-1, i, s-1) \frac{k-1}{2(s-1) + \frac{N_0}{m}}, \quad (8)$$

$$P(k, i, t) = \sum_{s=i+k-m}^t f(k, i, s) \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right). \quad (9)$$

Proof First, consider Eq. (8). The degree of vertex is nondecreasing, and increasing at most by 1 each time, according to the construction of the BA model. Thus, it follows from the Markovian properties that

$$\begin{aligned} f(k, i, s) &= P\{k_i(s) = k, k_i(l) \neq k, l = 1, 2, \dots, s-1\} \\ &= P\{k_i(s) = k, k_i(s-1) = k-1, k_i(l) \neq k, l = 1, 2, \dots, s-2\} \\ &= P\{k_i(s) = k, k_i(s-1) = k-1\} \\ &= P\{k_i(s-1) = k-1\} P\{k_i(s) = k | k_i(s-1) = k-1\} \\ &= P(k-1, i, s-1) \frac{k-1}{2(s-1) + \frac{N_0}{m}}. \end{aligned}$$

Second, observe that the earliest time for the degree of vertex i to reach k is at step $k+i-m$, and the latest time to do so is at step t . After this vertex degree becomes k , it will not increase any more. Thus, Eq. (9) is proved.

Lemma 6 Under the $m\Pi$ -hypothesis, in the BA model the limit $\lim_{t \rightarrow \infty} P(m, t)$ exists and is independent of the initial network; moreover,

$$P(m) \triangleq \lim_{t \rightarrow \infty} P(m, t) = \frac{2}{m+2} > 0. \quad (10)$$

Proof From the construction of the BA model or (2), it follows that

$$P(m, i, t+1) = \left(1 - \frac{m}{2t + \frac{N_0}{m}}\right) P(m, i, t).$$

Since $P(m, t+1, t+1) = 1$, one has

$$\begin{aligned} P(m, t+1) &= \frac{1}{t+1+m_0} \sum_{i=-m_0, i \neq 0}^{t+1} P(m, i, t+1) \\ &= \frac{t+m_0}{t+1+m_0} \left(1 - \frac{m}{2t + \frac{N_0}{m}}\right) P(m, t) + \frac{1}{t+1+m_0}. \end{aligned}$$

Then, iterative calculation yields

$$P(m, t) = \prod_{i=1}^{t-1} \left(1 - \frac{m}{2i + \frac{N_0}{m}}\right) \frac{i+m_0}{i+1+m_0} \left[P(m, 1) + \sum_{l=1}^{t-1} \frac{\frac{1}{l+1+m_0}}{\prod_{j=1}^l \left(1 - \frac{m}{2j + \frac{N_0}{m}}\right) \frac{j+m_0}{j+1+m_0}} \right]$$

$$= \frac{1}{t+m_0} \prod_{i=1}^{t-1} \left(1 - \frac{m}{2i + \frac{N_0}{m}}\right) \left[(1+m_0)P(m,1) + \sum_{l=1}^{t-1} \prod_{j=1}^l \left(1 - \frac{m}{2j + \frac{N_0}{m}}\right)^{-1} \right].$$

Next, let

$$x_n \triangleq (1+m_0)P(m,1) + \sum_{l=1}^{n-1} \prod_{j=1}^l \left(1 - \frac{m}{2j + \frac{N_0}{m}}\right)^{-1}$$

and

$$y_n \triangleq (n+m_0) \prod_{i=1}^{n-1} \left(1 - \frac{m}{2i + \frac{N_0}{m}}\right)^{-1} > 0.$$

It follows that

$$x_{n+1} - x_n = \prod_{j=1}^n \left(1 - \frac{m}{2j + \frac{N_0}{m}}\right)^{-1}$$

and

$$y_{n+1} - y_n = \frac{(m+2)n + \frac{N_0}{m} + mm_0}{2n + \frac{N_0}{m}} \prod_{i=1}^n \left(1 - \frac{m}{2i + \frac{N_0}{m}}\right)^{-1} > 0.$$

Consequently,

$$\frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{2n + \frac{N_0}{m}}{(m+2)n + \frac{N_0}{m} + mm_0} \rightarrow \frac{2}{m+2} \quad (n \rightarrow \infty).$$

It follows from Lemma 2 that

$$P(m) = \lim_{t \rightarrow \infty} P(m, t) = \lim_{n \rightarrow \infty} \frac{x_n}{y_n} = \lim_{n \rightarrow \infty} \frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{2}{m+2} > 0.$$

This completes the proof.

Lemma 7 Under the $m\Pi$ -hypothesis, in the BA model with $k > m$, if $\lim_{t \rightarrow \infty} P(k-1, t)$ exists, then $\lim_{t \rightarrow \infty} P(k, t)$ exists and, moreover,

$$P(k) \triangleq \lim_{t \rightarrow \infty} P(k, t) = \frac{k-1}{k+2} P(k-1) > 0. \quad (11)$$

Proof First, observe that

$$P(k, t) = \frac{1}{t+m_0} \sum_{i=-m_0, i \neq 0}^t P(k, i, t) = \frac{1}{t+m_0} \sum_{i=-m_0}^{-1} P(k, i, t) + \frac{t}{t+m_0} \frac{1}{t} \sum_{i=1}^t P(k, i, t).$$

Denote $\bar{P}(k, t) \triangleq \frac{1}{t} \sum_{i=1}^t P(k, i, t)$. One only needs to prove that the limit $\lim_{t \rightarrow \infty} \bar{P}(k, t)$ exists, which will imply that the limit $\lim_{t \rightarrow \infty} P(k, t) = \lim_{t \rightarrow \infty} \bar{P}(k, t)$ exists.

To show that the limit of $\bar{P}(k, t)$ exists as $t \rightarrow \infty$, observe that $P(k, i, t) = 0$ when $i > t + m - k$. Therefore, it follows from Lemma 5 that

$$\begin{aligned}
\bar{P}(k, t) &= \frac{1}{t} \sum_{i=1}^{t+m-k} P(k, i, t) \\
&= \frac{1}{t} \sum_{i=1}^{t+m-k} \sum_{s=i+k-m}^t f(k, i, s) \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right) \\
&= \frac{1}{t} \sum_{i=1}^{t+m-k} \sum_{s=i+k-m}^t P(k-1, i, s-1) \frac{k-1}{2(s-1) + \frac{N_0}{m}} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right) \\
&= \frac{1}{t} \sum_{s=k-m+1}^t \sum_{i=1}^{s+m-k} P(k-1, i, s-1) \frac{k-1}{2(s-1) + \frac{N_0}{m}} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right) \\
&= \frac{1}{t} \sum_{s=k-m+1}^t \sum_{i=1}^{s-1} P(k-1, i, s-1) \frac{k-1}{2(s-1) + \frac{N_0}{m}} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right) \\
&= \frac{1}{t} \sum_{s=k-m+1}^t \bar{P}(k-1, s-1) \frac{(s-1)(k-1)}{2(s-1) + \frac{N_0}{m}} \prod_{j=s}^{t-1} \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right) \\
&= \frac{1}{t} \prod_{i=k-m+1}^{t-1} \left(1 - \frac{k}{2i + \frac{N_0}{m}}\right) \left[\bar{P}(k-1, k-m) \frac{(k-1)(k-m)}{2(k-m) + \frac{N_0}{m}} \right. \\
&\quad \left. + \sum_{l=k-m+1}^{t-1} \bar{P}(k-1, l) \frac{l(k-1)}{2l + \frac{N_0}{m}} \prod_{j=k-m+1}^l \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right)^{-1} \right]
\end{aligned}$$

Next, let

$$\begin{aligned}
x_n &\triangleq \bar{P}(k-1, k-m) \frac{(k-1)(k-m)}{2(k-m) + \frac{N_0}{m}} \\
&\quad + \sum_{l=k-m+1}^{n-1} \bar{P}(k-1, l) \frac{l(k-1)}{2l + \frac{N_0}{m}} \prod_{j=k-m+1}^l \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right)^{-1}
\end{aligned}$$

and

$$y_n \triangleq n \prod_{i=k-m+1}^{n-1} \left(1 - \frac{k}{2i + \frac{N_0}{m}}\right)^{-1} > 0.$$

It follows that

$$x_{n+1} - x_n = \bar{P}(k-1, n) \frac{n(k-1)}{2n + \frac{N_0}{m}} \prod_{j=k-m+1}^n \left(1 - \frac{k}{2j + \frac{N_0}{m}}\right)^{-1}$$

and

$$y_{n+1} - y_n = \left[(n+1) - n \left(1 - \frac{k}{2n + \frac{N_0}{m}}\right) \right] \prod_{i=k-m+1}^n \left(1 - \frac{k}{2i + \frac{N_0}{m}}\right)^{-1}$$

$$= \frac{(k+2)n + \frac{N_0}{m}}{2n + \frac{N_0}{m}} \prod_{i=k-m+1}^n \left(1 - \frac{k}{2i + \frac{N_0}{m}}\right)^{-1} > 0.$$

By assumption,

$$\frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{(k-1)n}{(k+2)n + \frac{N_0}{m}} \overline{P}(k-1, n) \rightarrow \frac{k-1}{k+2} P(k-1) \quad (n \rightarrow \infty).$$

It then follows from Lemma 2 that

$$\lim_{t \rightarrow \infty} \overline{P}(k, t) = \lim_{n \rightarrow \infty} \frac{x_n}{y_n} = \lim_{n \rightarrow \infty} \frac{x_{n+1} - x_n}{y_{n+1} - y_n} = \frac{k-1}{k+2} P(k-1) > 0.$$

Thus, $\lim_{t \rightarrow \infty} P(k, t)$ exists and Eq. (11) is proved.

Theorem 2 Under the $m\Pi$ -hypothesis, the steady-state degree distribution of the BA model with $m \geq 2$ exists, and is given by

$$P(k) = \frac{2m(m+1)}{k(k+1)(k+2)} \sim 2m^2 k^{-3} > 0. \quad (12)$$

Proof By induction, it follows from Lemmas 6 and 7 that the steady-state degree distribution of the BA model with $m \geq 2$ exists. Equation (11) follows from iteration

$$P(k) = \frac{k-1}{k+2} P(k-1) = \frac{k-1}{k+2} \frac{k-2}{k+1} \frac{k-3}{k} P(k-3),$$

till $k = 3 + m$. Thus, one obtains

$$P(k) = \frac{2m(m+1)}{k(k+1)(k+2)} \sim 2m^2 k^{-3} > 0.$$

One can see that this degree distribution formula is consistent with the formula obtained by Dorogovtsev et al.^[6] and Bollobás et al.^[9], which allow multiple edges and loops.

Finally, the authors thank Professor Yirong Liu for many helpful discussions.

Z. Hou¹: zthou@csu.edu.cn
X. Kong¹: kongxiangxing2008@163.com
D. Shi^{1,2}: shidh2001@263.net
G. Chen³: gchen@ee.cityu.edu.hk